Towards a Query Translation Disambiguation Approach using Possibility Theory

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Abstract: We propose in this paper a combined method for Cross-Language Information Retrieval (CLIR) using statistical and lexical resources. On the one hand, we extracted a bilingual French to English dictionary from aligned texts of the Europarl collection. On the other hand, we built a co-occurrence graph structure and used the BabelNet lexical network to process the disambiguation of translation candidates for ambiguous words. We compared our new possibilistic approach with circuit-based one and studied the impact of query expansion by adopting the pseudo-relevance feedback (PRF) technique. Our experiments are performed using the standard CLEF-2003 collection. The results show the positive impact of PRF on the query translation process. Besides, the possibilistic approach using the co-occurrence graph outperforms the overall circuit-based runs.

1 INTRODUCTION

Cross-Language Information Retrieval (CLIR) deals with retrieving and ranking a set of documents written in a language different from the language of the user's query. It is an active sub-domain of the Information Retrieval (IR) which is centered on the search for documents starting from a need for information by the IR system user. Indeed, CLIR tries to overcome the language barrier between user requests and documents (Nie, 2010). In fact, in real life, a user submitting a query in French could also be interested in documents in English, German, Arabic, etc.

In order to solve the problem of linguistic heterogeneity, the intuitive solution consists in translating the query and/or the documents before performing the search. We distinguish three general approaches for translation that can be used in the design of a CLIR system (Zhou et al., 2012) depending on translating the query to match the representation of the document or translate the document to match the query or translate both of the query and the document to a third language called *pivot*.

The first method is the most widespread in CLIR researches since the length of the query is usually short which makes its translation faster and easier. However, the reduced length of the query may generate ambiguity effect due to a limited contextual information for the translation phase. Therefore, the second method of document translation retains the theoretical advantage of having more contextual information to determine the correct translation. However, given the volume of the documents, this translation becomes rather slow. This will require translating the documents into all possible languages.

The paper is organized as follows: We review in Section 2 previous related works about cross-lingual disambiguation. In Section 3, we present the model architecture that we used to perform translations disambiguation task. Section 4 details our new proposed possibilistic approach for query disambiguation. Experimental results and their discussion are provided in Section 5. Finally, Section 6 concludes this paper by evaluating our work and proposing some directions for future research.

2 RELATED WORK

The main approaches for query translation could be resumed in using a Machine Translation (MT) system or using a bilingual token-to-token resource (such as bilingual dictionaries) or relying on corpus analysis.

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Many barriers still challenge the development of CLIR systems such as the coverage of dictionaries, the unavailability of parallel corpora in some languages and common linguistic specificity like polysemy, agglutination and named entity recognition.

Parallel corpora are considered a common source of knowledge to perform the disambiguation task in multilingual context. By sharing hidden meaning that can be useful for extracting linguistic knowledge, these corpora are good resources not only for performing Cross-Lingual Word Sense Disambiguation (CLWSD), but also for Natural Language Processing (NLP) tasks (Resnik, 2004).

2.1 Graph-based Approaches for CLWSD

In general, many techniques have been addressed for solving CLWSD. As observed by (Duque et al., 2015), graph-based systems are one of the most successful approaches in the systems that participated in the 2010 and 2013 SemEval competitions. Some of these algorithms, have been widely used in the literature (Mihalcea, 2005; Navigli and Lapata, 2010; Agirre et al., 2014).

(Véronis, 2004) presented the HyperLex algorithm which is a corpus-based approach by building a co-occurrence graph for all pairs of words cooccurring in the context of the target word. This kind of graph have the properties of small world graphs. Hence, the graph possesses highly connected components (or hubs) that identify the main word uses (or senses) of the target word, and so can be used to perform WSD task.

Agirre et al. present in (Agirre et al., 2006) a comparative study between the Hyperlex algorithm of Véronis with an adapted algorithm of PageRank (Brin and Page, 1998) for WSD. Thus, they explored the use of two graph algorithms for corpus-based disambiguation of nominal senses. The performance of PageRank was nearly the same as that of HyperLex, with the advantage of PageRank of using less optimization parameters.

(Silberer and Ponzetto, 2010) was inspired by the works of (Véronis, 2004) and (Agirre et al., 2006). In fact, they presented in their work a graph-based system to perform CLWSD by using a co-occurrence graph built from multilingual parallel corpora and the application of previously developed graph algorithms for monolingual WSD. Afterwards, the Minimum Spanning Tree (MST) is extracted from the final graph to perform WSD.

(Duque et al., 2015) presented an approach which comprises the automatic generation of bilingual dictionaries and the construction of a co-occurrence graph to select the most suitable translations from the dictionary. The proposed algorithms are based on (i) sub-graphs (or communities) containing clusters of words with related meanings, (ii) distances between nodes representing words, and (iii) the relative importance of each node in the whole graph. Using the SemEval-2010 and SemEval-2013 datasets to evaluate their system, they proved the validity of the unsupervised graph-based technique, which uses the whole document as a coherent piece of information, while other works consider windows of a specific size for building the context and calculating the co-occurrences.

2.2 Combining Lexical and Statistical Resources for CLIR

Since there are a diversity of query translation techniques, the idea of combining these techniques was studied in recent works in order to examine if one approach is complementary to an other (Nie, 2010; Azarbonyad et al., 2013; Schamoni et al., 2014).

For example, (Herbert et al., 2011) introduced in a CLIR model by using Wikipedia to map concepts in one language to their equivalents in another language. This mapping is ensured thanks to the redirection and cross-language links in multilingual Wikipedia versions. In this work, the authors showed that the Wikipedia translations can improve the performance of statistical machine translation based CLIR systems. In fact, queries are translated with Google Translate online service and extended with new translations. These translations are obtained by mapping noun phrases in the query to concepts in the target language using Wikipedia.

(Türe and Boschee, 2014) have introduced a new method for building a single combination recipe for each query. They formulated this idea as a set of binary classification problems. The results show that trained classifiers can be used to produce query-specific combination weights effectively.

(Kim et al., 2015) explored how combining lexical and statistical translation resources can improve CLIR. Indeed, they used both Wikipedia and a machine readable dictionary (MRD) as lexical translation knowledge. Moreover, they explored parallel corpora to extract statistically the translation candidates. Kim et al. have proved that using the three translation evidences together (ie. a MRD, a parallel corpus and Wikipedia knowledge) can yield better results from any one source alone. Kim et al. proposed an approach to post-translation query expansion using a random walk over the Wikipedia concept link graph.

This approach yields further improvements over alternative techniques when evaluated on the NTCIR-5 English–Korean test collection.

A previous work of Elayeb et al. (Elayeb et al., 2017) try to adjust dictionary based query translation approaches since these approaches suffer from translation ambiguity and a word-by-word query translation is not always accurate. In this work, the authors proposed a probability-to-possibility transformation as a mean to introduce further tolerance in query translation process. The reported experiments on the CLEF-2003 test collection showed that the performance of the probability-to-possibility transformation based approach is better than the probabilistic one and some state-of-the-art CLIR tools. The work of Elayeb et al. was extended in (Ben Romdhane et al., 2017) to a discriminative possibilistic query translation disambiguation approach using both a bilingual dictionary and the Europarl parallel corpus. The main goal is to overcome some drawbacks of the dictionary-based techniques. When evaluated with the CLEF-2003 test collection, the discriminative possibilistic approach outperformed both the probabilistic and the probability-to-possibility transformation-based approaches, especially for short queries.

3 MODEL ARCHITECTURE FOR DISAMBIGUATING QUERY TRANSLATIONS

In this section, we propose the model architecture to design and implement a new approach for disambiguating query translations in CLIR. We present in Figure 1 the different resources and steps of this task as follows:

Starting from an initial query written in French (which presents the source language), a set of translations candidates in English language is reached from a specific built dictionary. The process of building this dictionary is described in sub-section 3.1.

Afterwards, the disambiguation module processes ambiguous words, which have more than one possible translation candidate. In this step, two main resources are used to choose only the most relevant translation (see details in sub-section 3.2).

A pseudo relevance feedback is applied at the end of the process by extracting the most significant terms from the top first returned documents and the whole process may be iterated.

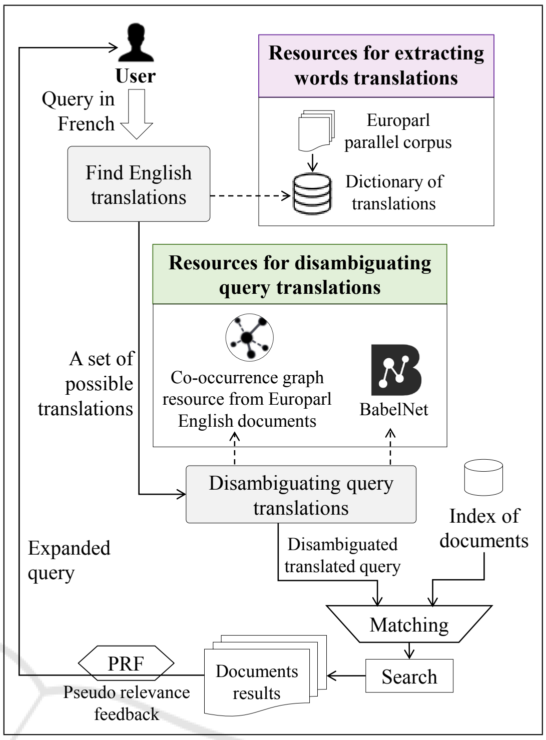

Figure 1: Overview of the disambiguation process for query translations.

3.1 Extracting Translation Candidates

To select the translation candidates for the query terms, we build a bilingual dictionary from the alignment of texts in French with the corresponding English texts in Europarl collection. This collection includes parallel texts in more than 11 languages which are extracted from the proceedings of the European Parliament (Koehn, 2005). Europarl was designed initially for the statistical machine translation (SMT). Nevertheless, it is used in other applications such as NLP and WSD.

Afterwards, to ensure the alignment of the parallel texts in Europarl at the word level, we used the GIZA++ statistical machine translation toolkit[1]. This tool is a statistical aligner that is able to extract one-to-many translations (Och and Ney, 2003).

The final extracted couples of word in both source and target languages are structured in CSV format. This format may help in making the dictionary an easy human readable resource. Nevertheless, the built resource lacks of coverage. Actually, we exploited a limited set of 717 French words enclosed in CLEF-2003 standard collection's queries (or topics). The final number of English translation candidates is 2324.

[1]http://www.statmt.org/moses/giza/GIZA++.html

Thus, extracting a limited subset of translations may lead to an Out Of Vocabulary (OOV) problem in case of using this resource for other more general purpose.

3.2 Disambiguating Query Translations

In order to proceed in disambiguation task of the proposed translation candidates after extraction step, we used two different types of resources: a statistical and a lexical resource. On the one hand, we extracted a co-occurrence graph from Europarl English documents. Each word is related with other words of the same sentence, based on the assumption that if two terms co-occur then they tend to be semantically related (Cao et al., 2005). Hence, we consider the sentence as the context window.

On the other hand, we used BabelNet, which is considered as a rich lexical resource by the integration of lexicographic and encyclopedic knowledge from WordNet and Wikipedia (Navigli and Ponzetto, 2012). BabelNet is a multilingual knowledge resource, in that it provides a semantic network where related concepts are connected within a graph structure. Given these distinguishing features, BabelNet is a powerful resource for performing knowledge-based lexical disambiguation in a multilingual setting. BabelNet groups words into sets of synonyms called *synsets* (this name is inspired from WordNet terminology (Miller et al., 1990)). All words composing a given Babel synset are semantically related.

4 A POSSIBILISTIC APPROACH FOR DISAMBIGUATING QUERY TRANSLATIONS

We based our approach on the possibilistic theory introduced by Zadeh (Zadeh, 1978) and developed by several authors (Dubois and Prade, 2011).

Consider we have a query written in source language $Q^{(src)} = \{T_1^{(src)}, T_2^{(src)}, \ldots, T_n^{(src)}\}$ where n represents the number of words in the query. Each term $T_i^{(src)}$ in the query may have one to many translation candidates in a chosen target language.

Let's note by $\Phi(T_i^{(src)}) = \{T_{ij}^{(trg)}, j \in [1..m]\}$ the set of the m possible translation candidates, for a term $T_i^{(src)}$, that are extracted from the built bilingual dictionary (refer to sub-section 3.1).

We call *vector of context*, relative to a term $T_i^{(src)}$, the union of sets of translation candidates for terms $T_k^{(src)} \neq T_i^{(src)}$ formalized as follows:

$$VC_i = \{\bigcup \Phi(T_k^{(src)}), k \neq i \, and \, k \in [1..m]\} \qquad (1)$$

We designate by *semantic vector*, relative to a translation candidate $T_{ij}^{(trg)}$, the set of extracted terms from the co-occurrence graph or the assembled synsets from BabelNet as described previously in subsection 3.2. Hence, we note the semantic vector as follows:

$$VS_{ij} = < s_{ij1}^{(trg)}, s_{ij2}^{(trg)}, \ldots, s_{ijk}^{(trg)} > \qquad (2)$$

The relevance of a semantic vector, presented by VS_{ij}, to the vector of context of the query, is determined by extending the possibilistic matching model proposed in (Ben Khiroun et al., 2012) by using a double measure of relevance as follows:

The *possible relevance* allows ignoring irrelevant translations to a given query. The *necessary relevance* reinforces the need to include relevant translation candidates in the final translation of the query.

The possibility measure $\Pi(VS_{ij}|VC_i)$ is proportional to:

$$\Pi(VS_{ij}|VC_i) \quad = \Pi(w_1|VS_{ij}) \times \ldots \times \Pi(w_p|VS_{ij}) \quad (3)$$
$$= nft_{1ij} \times \ldots \times nft_{pij}$$

- With: $nft_{kij} = tf_{kij}/max(tf_{kij})$ represents the normalized frequency of the translation term $w_k \in VC_i$ in the semantic vector VS_{ij} relative to the translation term candidate $T_{ij}^{(trg)}$;
- And $tf_{kij} = \frac{occurrences\, number\, of\, w_k\, in\, VS_{ij}}{number\, of\, terms\, in\, VS_{ij}}$.

The necessity to restore a relevant translation candidate $T_{ij}^{(trg)}$ for a context of translation terms, noted by $N(VS_{ij}|VC_i)$, is calculated as the following:

$$N(VS_{ij}|VC_i) = 1 - \Pi(\neg VS_{ij}|VC_i) \qquad (4)$$

At the same way, $\Pi(\neg VS_{ij}|VC_i)$ is proportional to:

$$\Pi(\neg VS_{ij}|VC_i) = (1 - \phi_1(T_{ij}^{(trg)})) \times \ldots \times (1 - \phi_p(T_{ij}^{(trg)})) \quad (5)$$

Where:

$$\phi_k(T_{ij}^{(trg)}) = Log_{10}(\frac{nCT_i}{nT_{ik}}) \times nft_{kij} \qquad (6)$$

- With: nCT_i: Number of translation candidates for the term $T_i^{(src)}$ of the initial query;
- And nT_{ik} : Number of translation candidates containing the term $w_k \in VC_i$.

We define the *degree of possibilistic relevance* (*DPR*) of each translation candidate ($T_{ij}^{(trg)}$) giving a context of translation terms (VC_i) by the following formula:

$$DPR(VS_{ij}|VC_i) = \Pi(VS_{ij}|VC_i) + N(VS_{ij}|VC_i) \quad (7)$$

The preferred translations are those having a high score of *DPR*.

We resume in Algorithm 1 the different steps of our proposed possibilistic approach.

Algorithm 1: The possibilistic algorithm for query translation disambiguation.

input : $Q^{(src)}$ query in source language
output: $Q^{(trg)}$ translated query in target language

foreach *term* $T_i^{(src)} \in Q^{(src)}$ **do**
  build vector of context VC_i
  foreach *translation candidate* $T_{ij}^{(trg)} \in \Phi(T_i^{(src)})$ **do**
    extract semantic vector VS_{ij} from a resource
    compute possibilistic score of VS_{ij} in relation with VC_i
  end
  add best translation candidate to $Q^{(trg)}$
end

5 EXPERIMENTAL RESULTS AND COMPARATIVE STUDY

In this section, we evaluate and compare the contribution of the possibilistic approach by using lexical and statistical translation resources. We used the CLEF-2003 as standard test collection. This collection provides necessary tools for the evaluation of information retrieval systems for mono- and multilingual tasks. It includes a set of documents, a set of queries and the list of relevant documents for each query (Braschler and Peters, 2004). The documents, that form CLEF-2003, are written in 9 European languages (including English and French) and are collected from the same periods and have comparable contents.

To perform the experimentation, we used the Terrier platform for information retrieval. All experiments are carried out using the OKAPI BM25 weighting model for matching between queries and documents (Ounis et al., 2007).

5.1 Evaluating the Query Translation Approach

We compare in Figure 2 our proposed approach for disambiguating query translations based on two knowledge resources. The series, labeled with "Cooccurrence" and "Babelnet", refer respectively to the co-occurrence built graph scenario and to synsets extracted from BabelNet.

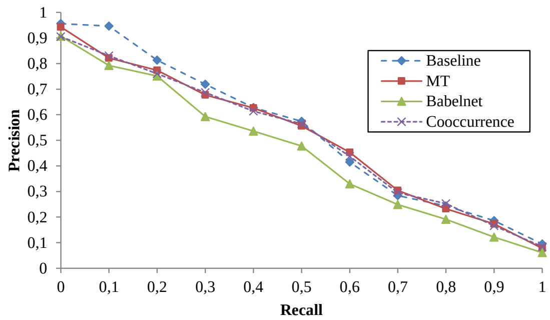

Figure 2: Recall-Precision curve comparing different runs.

The "baseline" series represent the precision of the original English version of queries proposed in CLEF-2003 test collection. We introduced also the results of translations using the *Google Translate* Machine Translation (MT) tool (https://translate.google.com).

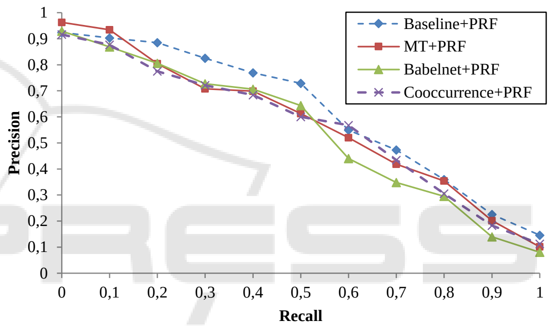

Figure 3: Recall-Precision curve comparing different runs by applying pseudo-relevance feedback (PRF).

The pseudo-relevance feedback (PRF) technique exploits the top k most relevant retrieved documents in order to expand the proposed query. Therefore, a set of candidate terms from these documents is added using often variants of Rocchio algorithm (Rocchio, 1971). Hence, we present, in Figure 3, the impact of applying PRF with previous runs scenarios. We used the Bo1 (*Bose-Einstein 1*) PRF algorithm implemented in the Terrier IR platform by applying the default settings as follows: the number of terms to expand a query is set to 10 and the number of top-ranked documents from which these terms are extracted is limited to three documents.

Table 1 details precision values @5, @10, @15... and @1000 top documents of all runs by applying the PRF query expansion. Results show that using co-occurrence as a disambiguating resource by applying the possibilistic approach outperform other resources at first top documents. However, the performance of MT is better at last ranked documents.

To refine our study about the co-occurrence based approach in comparison with the BabelNet

Table 1: Precision values for different runs by applying pseudo relevance feedback.

	Baseline	MT	BabelNet	Co-occurr.
P@5	0,4148	0,3741	0,3741	**0,3815**
P@10	0,3333	0,3259	0,3037	**0,3352**
P@15	0,2975	0,2864	0,2691	**0,3012**
P@20	0,2741	0,2657	0,2398	**0,2759**
P@30	0,2309	0,2259	0,2049	**0,2364**
P@50	0,1785	0,1789	0,1596	**0,1848**
P@100	0,118	**0,1185**	0,1056	0,1174
P@200	0,0705	**0,0694**	0,065	0,0683
P@500	0,0334	**0,0315**	0,0304	0,0313
P@1000	0,0175	**0,0164**	0,0162	0,0163

and the machine translation approaches, we use the *Wilcoxon* matched-pairs signed-ranks test as proposed by (Demšar, 2006). The given values (*p value*) are computed by comparing the precision values pairs of the co-occurrence based resource approach to each from the other machine translation and BabelNet based approaches.

As given in Table 2, the *p value* results prove that the improvement of the co-occurrence approach, compared to both the MT (*p value* = 0.010301 $<$ 0.05) and to the BabelNet (*p value* = 0.003509 $<$ 0.05), is statistically significant (Biau et al., 2010).

Table 2: The p value results for the Wilcoxon matched-pairs signed-ranks test for precision values.

	p value
Co-occurrence vs. MT	0.010301
Co-occurrence vs. BabelNet	0.003509

In order to have a comparison study of the possibilistic model, we conducted more detailed experiments by using the circuit-based approach measure. This approach was studied previously in monolingual WSD by (Elayeb et al., 2015).

In our current work, we apply this model for disambiguating query translations terms by computing semantic similarity of a given term t_i and a translation candidate t_j according to the following formula:

$$sim(t_i,t_j) = \frac{\#circuits(t_i,t_j)}{MAX(\#circuits\,in\,graph)} \quad (8)$$

- Where: $\#circuits(t_i,t_j)$: represents the number of circuits starting from the node t_i and passing through the node t_j in the graph (i.e. $t_i \to \ldots \to t_j \to \ldots \to t_i$);
- And: $MAX(\#circuits\,in\,graph)$: represents the maximum number of circuits in the graph.

Aiming to optimize the search of circuits in the graph structure, we extracted a limited collection of BabelNet's synsets included in the translation candidates. This subset covers only the dictionary of translations entries that corresponds to CLEF-2003 queries. Besides, we considered the maximum length of circuit taken into account about 4 edges as studied in (Elayeb, 2009).

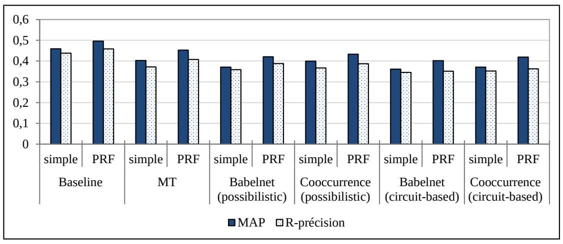

Figure 4: MAP and R-precision results for possibilistic and circuit-based approaches by applying pseudo relevance feedback (scenario “PRF”) and without applying it (scenario “simple”).

Figure 4 shows the values of the MAP and R-precision common measures in the evaluation of IR systems. The MAP value represents the mean average precision of the query topics and the R-precision defines the precision at rank R; where R is the total number of relevant documents (Baccini et al., 2012)

As a general first observation, we notice that the co-occurrence methods still outperform with little enhancement the BabelNet based runs. However, all runs are under baseline and MT performance when considering the MAP an R-precision metrics.

Results show an advance for possibilistic runs when compared to the circuit-based approaches. Indeed, computing the DPR score comprises two measures: the possible relevance allows rejecting irrelevant translations, whereas the necessary relevance makes it possible to reinforce the translations not eliminated by the possibility. The performance of possibilistic models versus probabilistic ones was also observed in other applications such as query expansion (Elayeb et al., 2011) and monolingual WSD (Elayeb et al., 2015).

6 CONCLUSION

This work presents and compares possibilistic and circuit-based approaches using statistical and lexical resources. The two resources are built by modeling co-occurrence graph and extracting BabelNet synsets relations to form graph data structures. Our proposed approach aim to design a general process for CLWSD.

On the one hand, the proposed possibilistic approach outperformed the circuit-based one. On the other hand, using co-occurrence graphs have resulted to slightly better performance compared to exploiting extracted sub-networks from BabelNet. Furthermore, applying pseudo-relevance feedback technique contributed in the enhancement of different runs, which joins previous works (Paskalis and Khodra, 2011; Ben Khiroun et al., 2014; Elayeb et al., 2014).

As future perspectives of the current work, we propose to resolve the out of vocabulary problem due to the nature of bilingual dictionary extraction process that is proposed in this paper. In fact, knowledge based query translation approaches that rely on aligned corpora are dependent to the size and the type of analyzed texts. This could be a great challenge face to the lack of parallel resources for some languages like Arabic as presented in (Elayeb and Bounhas, 2016). Another potentially interesting direction for future work would be to study the impact of applying query expansion before and after the translation process (known also by pre- and post-translation query expansion). Moreover, we can study the contribution of query expansion techniques, other than pseudo-relevance feedback, such as knowledge based ones that rely on machine readable dictionaries or by exploiting ontological semantic relations for example.

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